



Assessing the Impact of Future Personalised Public Transport

Jiang, Yu; Ceder, Avishai

Publication date:
2018

Document Version
Publisher's PDF, also known as Version of record

[Link back to DTU Orbit](#)

Citation (APA):
Jiang, Y., & Ceder, A. (2018). *Assessing the Impact of Future Personalised Public Transport*. Paper presented at Conference on Advanced Systems in Public Transport .

General rights

Copyright and moral rights for the publications made accessible in the public portal are retained by the authors and/or other copyright owners and it is a condition of accessing publications that users recognise and abide by the legal requirements associated with these rights.

- Users may download and print one copy of any publication from the public portal for the purpose of private study or research.
- You may not further distribute the material or use it for any profit-making activity or commercial gain
- You may freely distribute the URL identifying the publication in the public portal

If you believe that this document breaches copyright please contact us providing details, and we will remove access to the work immediately and investigate your claim.

Assessing the Impact of Future Personalised Public Transport

Yu Jiang · Avishai (Avi) Ceder

Abstract The purpose of this study is to assess the potential impact of future personalised public transport (PT) services allowing a traveller to communicate with an information provider using specific personal preferences when undertaking a trip. Our methodology is based on finding the K-shortest path for travellers where the value of each link comprises the cost of the various weighted factors based on users' preferences, and assigning travellers to a path set according to service frequency and path cost. Case studies were conducted using the Copenhagen Central Network. It was found that, for instance, future personalised PT, could reduce user travel cost by 5.91%.

Keywords: Personalised Public Transport · Smartphone Guidance· K-shortest Path· Transit Assignment.

1 Introduction

Public transport (PT) is a key element in most major cities around the world. With the development of smartphones, real-time and readily available journey planning information is becoming an integral part of the PT system. The information might not only be better to inform traveller's trip plan, but also allows a traveller communicating about his/her specific preferences when undertaking a trip.

PT travellers are likely to have preferences over different features of a journey, that might even influence their travel decisions including modal choice and route choice. A number of factors/attributes have been found to be important in affecting

Yu Jiang
Transport DTU, Danmarks Tekniske Universitet (DTU),
Lyngby, Denmark
Email: yujiang@dtu.dk

Avishai (Avi) Ceder
Faculty of Civil and Environmental Engineering, Technion-Israel Institute of Technology,
Haifa, Israel. And
Department of Civil and Environmental Engineering, The University of Auckland
Auckland, New Zealand
Email: a.ceder@auckland.ac.nz

passengers' choice, such as the quality of a PT service, connectivity, fare cost, accessibility, and journey distance (e.g., Kingham et al. 2001, Galdames et al. 2011; Ceder and Teh, 2010). These factors or attributes could play a major role in determining PT route choices (Ceder et al. 2013; Ceder, 2016; Grison et al. 2017). Moreover, passengers' preferences over these attributes could vary depending on various factors, such as time of day, mood, schedule to follow, family issue, etc. Therefore, every trip a user makes has unique requirements. Accordingly, a well-designed smartphone application should allow for travellers to interact with the operator in term of sending preferences and receiving tailored information. In the last few years and recently an increased attention was and is given for informative and to some extent personalised smartphone applications by the industry and researchers (e.g., Global Mass Transit 2014; Shaheen et al. 2016).

Generally speaking, as per Chorus (2012), a personalised smartphone application can be beneficial from two perspectives: (i) The services remember and learn from the travellers' choice profile and allow us to predict travellers' mobility or to issue context-sensitive personal advice (Lathia et al. 2013; Bouhana et al. 2013; Arentze 2013); and (ii) The services consider travellers' preferences over different attributes (i.e., Peng and Huang, 2000; Zografos et al. 2009; Chorus et al. 2009).

The focus of this study is perspective (ii) and the objectives are threefold. First, it proposes a methodology based on the K-shortest path to model future personalised PT services, which consider travellers' preferences of different PT attributes in the route guidance. Second, it develops a corresponding transit assignment model to predict the usages for the future PT services. Finally, it applies the route-guidance and transit assignment model to assess the potential impacts of future personalised PT services.

2 Methodology

In traditional smartphone applications, users are given a set of paths and might select to sort the paths using given attributes, such as travel time (i.e., Google map), and possibly with a boundary related to an attribute, such as the maximum number of transfers (i.e., Rejseplanen App in Denmark). These apps, to some extent, cater passengers' preferences for different PT attributes, but cannot capture the trade-off between the various attributes and the stochasticity involved with passengers' preferences across time, space, weather, importance, mood, etc. In contrast, a future personalised smartphone application should allow for passengers to indicate, at the time of a need for a ride, their preferences of different attributes and in return to obtain a set of best-recommended routes/paths. To model this, we propose to use a weighted travel cost incorporating various PT attributes and to use a K-shortest path algorithm to determine a set of paths adaptable to users' preferences. To attain this goal, passengers' route choice behaviour is taken also into account by developing a transit

assignment model based on the K-shortest path concept. The overall framework of our analytical approach is illustrated in Figure 1.

From a user's perspective, a traveller could assess various PT-service information provided by the operator and specify the relative importance of different attributes of his/her route choice decision made via a smartphone. Given these parameters, a pathfinding component returns K-shortest path options to be displayed on the traveller's smartphone application. Considering passengers' real-time demand and the computational algorithmic effort, we suggest computing the K-shortest path for all OD pairs offline and storing the resultant path sets in a database. For the offline computing, we could set all attributes equally important or calibrate these parameters from survey data.

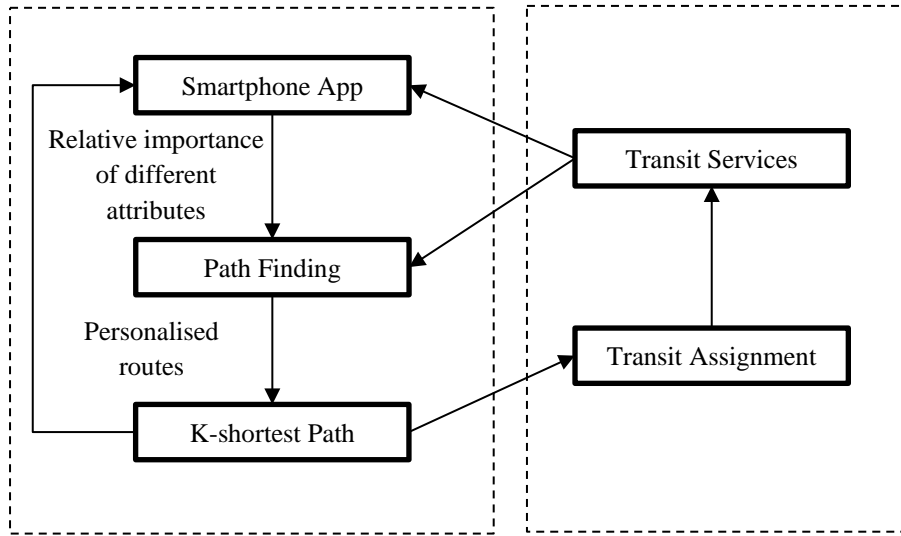


Fig. 1 Framework

In real-time scenarios, the input of preferences is used to update the weighted costs of the K-shortest path and obtain a new order of best recommended. At the same time, the set of best paths is utilised in a transit assignment model to predict the usages of PT services upon which the operator could implement operational tactics for improving the level of service provided.

The mathematical formulations encapsulated in the analysis framework are briefly elaborated as follows.

$$d_{ij} = \sum_m \alpha^m c_{ij}^m, \forall ij \quad (1)$$

$$\pi_p^{od} = \sum_{ij} \delta_{ij}^p d_{ij}, \forall od, p \quad (2)$$

$$x_p^{od} = \frac{f_{l_p}}{\sum_{l \in L_{od}} f_l} \frac{\exp(-\theta \pi_p^{od})}{\sum_{p \in \Omega_p^{od}} \exp(-\theta \pi_p^{od})} g^{od}, \forall od, p \in P_k^{od} \quad (3)$$

Equation (1) defines the weighted link cost d_{ij} , where c_{ij}^m is attribute m associated with link ij and α^m is the weighting parameter applied to attribute m based on users' preferences. Equation (2) computes the weighted travel cost of path p connecting nodes o and d . Equation (3) depicts the transit assignment model given the K-shortest path set P_k^{od} , where x_p^{od} denotes the number of passengers travelling on path p ; f_{l_p} represents the frequency of the first PT service associated with path p ; L_{od} denotes the set of transit lines departing from node o ; Ω_p^{od} is the set of paths that starting with the same PT service; g^{od} is the travel demand between nodes o and d . The assignment model assumes that each passenger has a set Ω_p^{od} of attractive paths (based on the K-shortest path procedure's outcome) and boards the first PT vehicle associated with these paths. In case the first PT vehicle is utilised by more than one paths, the passenger is then assigned to a path using logit model. That is, this passenger will use the first arrived PT vehicle, but will use different transfers than the case in which the vehicle won't be utilised by other paths.

In the K-shortest path algorithm, the weighted factors are associated with an individual user, who uses a smartphone application to set his/her preferences. However, for the assignment model, an operator is more interested in the aggregated flow distribution instead of disaggregated route choice. Thus, in line with Nielsen (2000), we adopt a simulation procedure to generate various passengers' preferences to compute average flows.

3 Case Study

The methodology developed was applied for the Copenhagen Central Area shown in Figure 2. The Greater Copenhagen is divided into 99 zones. The studied area contains Copenhagen's Zones 1, 2, 3, and half of 4, which cover most of central Copenhagen city. All PT services operated between 7 am and 9 am are included. The frequencies of the PT services were approximated based on the latest-possible timetable information of the fall of 2014. The demand data includes all trips between 7 am and 9 am. In short, there are 278 PT lines, 397 stops, and 27078 OD pairs. The program was coded in C# and run on a laptop with Intel(R) Core(TM) i5-3380M CPU @2.90GHz.

The first experiment was designed to examine the significance of using a personalised smartphone application. Two experiments were constructed. In the first experiment passengers were assumed to select the shortest path without considering their preferences. In the second experiment it was assumed that these passengers indicate

their preferences using a smartphone application, and that the application displays the K-shortest path based on a weighted path cost. The first experiment resembles the usage of a traditional application; the second experiment represents a future personalised application. Without a loss of generality, preferences were randomly generated for each OD pair and set to be identical for the two experiments. For simplicity the analysis focuses on the weighted cost of the 1st path of the recommended path set. Our results reveal that, in an average sense, passengers of the second experiment could reduce their weighted travel cost by 5.91%.

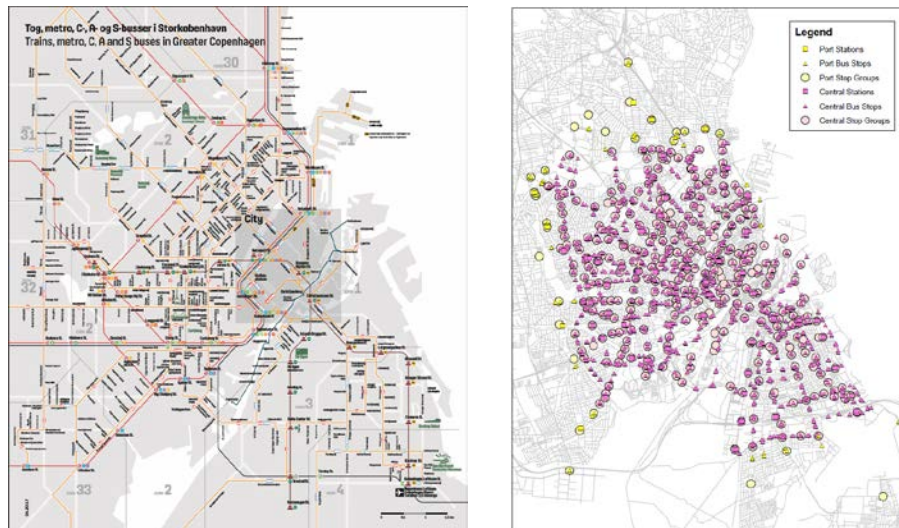


Fig.2 Copenhagen Central Network (Zones 1, 2, 3 and 4)

The second experiment was designed to test the robustness of the methodology using 1000 simulation runs. The results show that the average cost reduction of all 1000 runs is 5.94%. The maximum, minimum, and the standard deviation of the cost reduction are 6.19%, 5.64% and 0.08%, respectively. These results confirm that the proposed methodology is robust, and its performance is stable in terms of reducing the weighted path cost for a large network.

4 Conclusions and Future Research

This study developed a methodology to model future personalised PT services based on finding the K-shortest path of travellers where the value of each link is comprised of the cost of the various weighted factors representing the users' preferences. Meanwhile, a logit based transit assignment model was proposed to predict travellers route choice. The modelling framework was applied to assess the impact of the personalised PT services in the Copenhagen Central area. It demonstrates that passengers could reduce their weighted travel cost by 5.91%, and the personalised PT is robust in reducing the weighted travel cost.

Given the technology available, the high use of smartphone devices, and the potential for user preferences to be taken into account, it is recommended that further research consider the following points:

- Application of the methodology with a stochastic shortest and K-shortest path algorithm to understand the variance in PT trips that occur in reality and incorporate passengers' risk-aversion attitude in the transit assignment model (Jiang and Szeto, 2016).
- Extend the options provided to users to cater for more real-time elements such as passengers' load profiles and network congestion.
- Undertake a case study using more data to ensure the adequacy of the methodology.

Acknowledgements: This work is partly funded by the Innovation Fund Denmark (IFD) under File No. 4109-00005

References

- Arentze, T.A. (2013). Adaptive personalised travel information systems: A Bayesian method to learn users' personal preferences in multimodal transport networks. *IEEE Transactions on intelligent transportation systems*, 14(4), 1957-1966.
- Bouhana, A., Fekih, A., Abed, M., Chabchoub, H. (2013). An integrated case-based reasoning approach for personalised itinerary search in multimodal transportation systems. *Transportation Research Part C*, 31, 30-50.
- Ceder, A. (2016). *Public Transit Planning and Operation: Modeling, Practice and Behavior*, Second edition, CRC Press, Boca Raton, USA.
- Ceder, A., Teh., C.S. (2010). Comparing Public-Transport Connectivity Measures among Major Cities (in New Zealand). *Transportation Research Record: Journal of the Transportation Research Board*, No. 2143, 24-33.
- Ceder, A., Chowdhury, S., Taghipouran, N., Olsen, J. (2013). Modelling public-transport users' behaviour at connection point. *Transport Policy*, 27, 112-122.
- Chorus, C.G. (2012). Travel Information: Time to Drop the Labels?. *IEEE Transactions on Intelligent Transportation Systems*, 13(3), 1235-1242.
- Chorus, C.G., Arentze, T.A., Timmermans, H.J. (2009). Traveler compliance with advice: A Bayesian utilitarian perspective. *Transportation Research Part E*, 45(3), 486-500.
- Galdames, C., Tudela, A., Carrasco, J.A. (2011). Exploring the role of psychological factors in mode choice models by a latent variables approach. *Transportation Research Record: Journal of the Transportation Research Board*, 2230, 68-74.
- Global Mass Transit report, 2014. Smartphone Applications in Transit Services: Growing Popularity. Retrieved from <http://www.globalmasstransit.net/archive.php?id+16210>, 30 June 2016.
- Grison, E., Burkhardt, J.M., Gyselinck, V. (2017). How do users choose their routes in public transport? The effect of individual profile and contextual factors. *Transportation Research Part F*, 51, 24-37.

-
- Jiang, Y., Szeto, W.Y. (2016). Reliability-based stochastic transit assignment: Formulations and capacity paradox. *Transportation Research Part B*, 93, pp. 181-206.
- Kingham, S., Dickinson, J., Copsey, S. (2001). Travelling to work: will people move out of their cars. *Transport policy*, 8(2), 151-160.
- Lathia, N., Smith, C., Froehlich, J., Capra, L. (2013). Individuals among commuters: Building personalised transport information services from fare collection systems. *Pervasive and Mobile Computing*, 9(5), 643-664.
- Nielsen, O.A. (2000). A stochastic transit assignment model considering differences in passengers' utility functions. *Transportation Research Part B*, 34(5), 2000, 377-402.
- Peng, Z.R., Huang, R. (2000). Design and development of interactive trip planning for web-based transit information systems. *Transportation Research Part C*, 8(1), 409-425.
- Shaheen, S., Martin, E., Cohen, A., Musunuri, A., Bhattacharyya, A. (2016). *Mobile Apps and Transportation: A Review of Smartphone Apps and a Study of User Response to Multimodal Traveler Information*. Final report, ITS of UC Berkeley, California Department of Transportation (Caltrans), October.
- Zografos, K.G., Androusoyopoulos, K.N., Spiliadakis, V. (2009). Design and assessment of an online passenger information system for integrated multimodal trip planning. *IEEE Transactions on Intelligent Transportation Systems*, 10(2), 311-323.